Optimal control of greenhouse climate using Genetic Algorithms

Hartmut Pohlheim[1] and Adolf Heißner[2]

Technical University Ilmenau, Faculty of Informatics and Automation,
PSF 327, 98684 Ilmenau, Germany, pohlheim@systemtechnik.tu-ilmenau.de[1]
Institut für Gemüse- und Zierpflanzenbau Großbeeren/Erfurt e.V.
Theodor-Echtermeyer-Weg 1, 14979 Großbeeren, Germany[2]

Abstract. To understand greenhouse systems complex models are used increasingly. This paper presents an integrated model incorporating all components of a greenhouse: greenhouse climate, crop growth, outside weather conditions and control equipment. The model predicts temperature, air humidity and CO_2 concentration in a time interval of 15-60 minutes. This model can be used for short time tasks as maximization of growth or prevention of stress. Using genetic algorithms the control is optimized for maximal profit. The results of optimization for optimal control during three average days and different control strategies by changing costs of control are shown.

1 Introduction

Crop growth and yield models as well as greenhouse climate models are essential to understand, control and optimize the components in a greenhouse ([2], [5], [6], [14], [16], [23]). Current research led to the development of strategies for the further enhancement of greenhouse climate control. By simulation and in research greenhouses the advantage of such models could be shown compared to control using fixed setpoints ([1], [3], [10], [13], [17], [22]).

Previously published solutions are often limited to the modeling of single components as temperature or CO_2 concentration. This restricts the possible application. The control of the different technical elements cannot be done independently. For example, ventilation influences temperature, humidity and CO_2 concentration at the same time. This should be considered in the models.

Based on this demand a model was formulated for the prediction of temperature, air humidity and CO_2 concentration in a time interval of 15 to 60 minutes. This model can be employed for short time control tasks as maximization of crop growth or the prevention of stress.

Section 2 describes the greenhouse climate model together with a plant model (here tomato). In Section 3 simulation and optimization are outlined, especially genetic algorithms. The executed optimizations are represented in Section 4. Section 5 gives concluding remarks and some prospect directions of further investigations.

2 Greenhouse climate model

The greenhouse climate model, Fig. 1, describes the dependence of temperature, air humidity and CO_2 concentration inside the greenhouse on the outside weather conditions and the control equipment using 3 nonlinear differential equations of first order.

The 3 differential equations of the model are the balance equations of the greenhouse interior for 1) energy (temperature), eq. 1, 2) vapor (air humidity), eq. 2 and 3) CO_2 (CO_2 concentration), eq. 3.

The greenhouse climate can be influenced by 4 control components: 1) heating, Q [W/m²], 2) ventilation, LR [m³/m²], 3) CO_2 enrichment, W [g/(m²·h)] and 4) vapor injection, RM [g/(m²·h)].

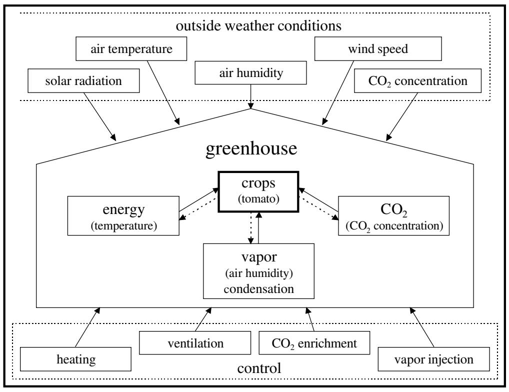

Fig. 1: Scheme of greenhouse climate model

The outside weather conditions to be measured are 1) solar radiation, $IGLOB$ [W/m^2], 2) air temperature outside, $TEMA$ [°C], 3) air humidity outside, FA [% r.F.], 4) CO_2 concentration outside, CA [ppm] and 5) wind speed, U [m/s].

The greenhouse model uses only one compartment (interior of the greenhouse including plants), thus, additional input values have to be considered: 1) floor temperature, *TEMB* [°C] and 2) cover temperature, *TEMG* [°C].

Both values can be measured. Another possibility (used here) is the derivation of the values on the outside weather conditions and the inside climate through a regression model.

The temperature used in the balance equations is determined by the specific heat capacity of air and plants in the greenhouse. Thus, the temperature is the average of air and plant temperature.

The computation of the model uses a number of physical constants, greenhouse parameters as well as coefficients for the description of transpiration ([11]) and CO_2 gas exchange ([12]) by models and plant parameters. Due to space limitations this paper outlines the model. For an extended description, all parameters and equations as well as an explanation of all variables refer to [19].

2.1 Greenhouse balance equations

2.1.1 Energy balance

The energy balance, *DTEMI* [K/s], Fig. 2, is represented by: 1) heat injection by heating, *Q*, 2) warming by solar radiation, *qglob*, 3) change of air humidity, *DDDI*, 4) heat exchange with environment by ventilation, *qluwe*, 5) heat lost through cover, *qduga*, 6) heat exchange at floor, *qboden*, 7) condensation or evaporation at cover, *qkonden* and 8) heat capacity of greenhouse (plants, air inside), *CG*.

$$DTEMI=(1/(CG+GH \cdot CPD \cdot DDI)) \cdot (Q+qglob-qluwe-qduga-qboden-qkonden-GH \cdot (VDW0+CPD \cdot TEMI) \cdot DDDI). \quad (1)$$

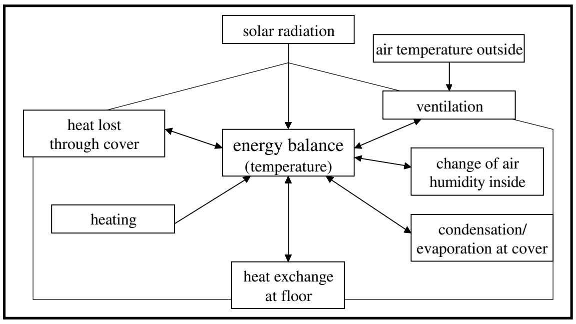

Fig. 2: Scheme of energy balance

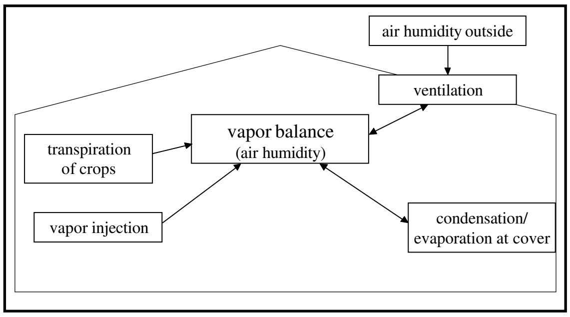

Fig. 3: Scheme of vapor balance

2.1.2 Vapor balance

The vapor balance/density, *DDDI* [g/(m^3·s)], Fig. 3, is represented by: 1) transpiration of plants, *trans*, 2) vapor injection, *lube*, 3) vapor exchange with environment by ventilation, *wadawe* and 4) condensation or evaporation at cover, *kondverd.*

$$DDDI= (1/(GH \cdot 3600)) \cdot (trans+lube-wadawe-kondverd). \quad (2)$$

Condensation (evaporation) at the cover appears, if the value of konden is positive (negative). Condensation is always possible. If the maximal condensation density is exceeded the condensation is flowing down at the cover. Evaporation can only appear, if there is condense at the cover.

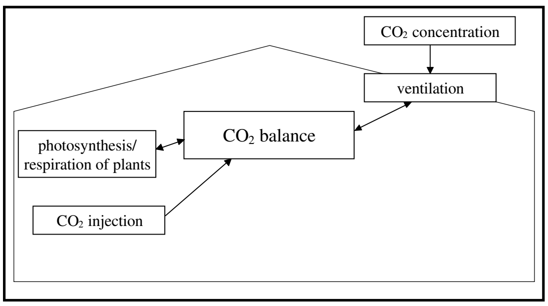

Fig. 4: Scheme of CO_2 balance

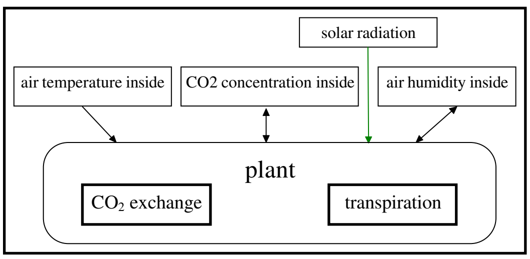

Fig. 5: Scheme of plant model

2.1.3 CO_2 balance

The CO_2 balance, *DCI* [ppm/s], Fig. 4, is represented by: 1) CO_2 enrichment, *W*, 2) CO_2 exchange of plants, *gawe* and 3) CO_2 exchange with environment by ventilation, *kodiwe*.

$$DCI = (W - gawe - kodiwe) \cdot (1/(10^{-6} \cdot DC \cdot GH \cdot 3600)). \tag{3}$$

2.2 Plant balance equations (tomato)

2.2.1 CO_2 exchange of plants

The CO_2 exchange of the plant canopy, *gaweblfl* [mg/(dm²·h)], Fig. 5, is related to the CO_2 exchange under standard conditions (P_0: standard CO_2 exchange rate):

$$gaweblfl = P_0 \cdot FICT \cdot FSD. \tag{4}$$

The value of *FICT* is calculated by a parametric equation:

$$FICT = C_1 \cdot (1-\exp(-C_2 \cdot 0.5 \cdot I)) \cdot (1-\exp(-C_3 \cdot CI)) \cdot (TEMI + C_4 \cdot TEMI^2) - C_5 \cdot (TEMI + C_6 \cdot TEMI^2).$$

The value of *FSD* is calculated by 3 equations. Which one to use depends on the value of the humidity saturation deficit, *SDI*:

$$SDI < SDIG_1 \qquad FSD = \exp(EE_1 \cdot (SDIG_1 - SDI)^2)$$
$$SDIG_1 \le SDI \le SDIG_2 \qquad FSD = 1$$
$$SDI > SDIG_2 \qquad FSD = \exp(EE_2 \cdot (SDIG_2 - SDI)^2)$$

2.2.2 Transpiration

The transpiration of the leaf area, *trblfl* [g/(dm²·h)], Fig. 5, is related to the transpiration under standard conditions (V_0: standard transpiration rate):

$$trblfl = V_0 \cdot VREL. \tag{5}$$

The value of *VREL* is calculated by 3 parametric equations:

$$VREL = VRELC \cdot SDI \cdot (B_1 + B_2 \cdot I + B_3 \cdot I^2 + B_4 \cdot (PDI/PSI) \cdot 100)/VSTAN,$$
$$VRELC = 1 - B_0 \cdot (CI - 600),$$
$$VSTAN = 10 \cdot (B_1 + B_2 \cdot 300 + B_3 \cdot 3002 + B_4 \cdot 60).$$

2.3 Biomass and profit

The profit, *GEWI* [0.01 DM/(m²·h)] is represented by: 1) biomass, *BIOM*, 2) fruit price, PR_1, 3) cost of CO_2 enrichment, PR_2, and 4) cost of heating, PR_3.

The biomass, *BIOM*, is calculated by the CO_2 exchange of the plants, *gawe*. The biomass is converted into yield. The cost for CO_2 enrichment is calculated from the price of CO_2 and the price for heating from the price of oil.

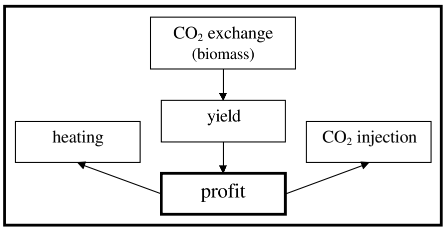

Fig. 6: Scheme of profit calculation

$$GEWI = (BIOM \cdot 10^{-2} \cdot PR_1 - W \cdot PR_2 \cdot 10^3 - Q \cdot PR_3) \cdot 10^2; \quad BIOM = gawe \cdot \tfrac{30}{44}. \tag{6}$$

components	symbol	unit	function
biomass	*BIOM*	g/(m²·h)	gawe·(30/44)
fruit price	PR_1	DM/kg	3
CO_2 price	PR_2	DM/kg	1
energy price	PR_3	DM/(W·h)	0.00005

Tab. 1: Components of profit calculation

2.4 Constraints

The constraints of the controls are defined by the boundaries of the domain of the control variables: heating [0...150 W/m^2]; air ventilation [2...100 m^3/(m^2·h)] and CO_2 enrichment [0...10 g/(m^2·h)]. Vapor injection is not used currently.

The states of the greenhouse climate are constrained to prevent stress from the plants. Currently we employ constraints for the temperature in the greenhouse. The temperature should always be above 16°C and if possible not higher than 24°C.

2.5 Simulation

The greenhouse climate model is a set of first-order differential equations. Using the initial values of the variables of the differential equations the system has a solution for a final point. The simulation/integration of these equations solves the system over a given time period.

We used an embedded RUNGE-KUTTA method of 4th(5th) order for the integration of the greenhouse climate model.

3 Description of the optimization algorithm

3.1 Survey

For the greenhouse climate model a control should be calculated. Thus, methods of dynamic optimization or optimization of dynamic systems must be used.

We used genetic algorithms, an alternative to deterministic optimization algorithms. Genetic algorithms differ from deterministic search methods (for instance gradient methods) mainly in the manner in which variables are changed. Whereas gradient methods change the variables according to deterministic rules, genetic algorithms are based on random transition rules.

This Section gives a short introduction to genetic algorithms. For an in deep discussion of genetic algorithms refer to [18] and [21].

Genetic algorithms model natural processes, such as populations, selection, recombination, mutation and migration. Genetic algorithms work on populations of individuals instead of single solutions. In this way the search is performed in a parallel manner.

At the beginning of the computation a number of individuals (the population) are randomly initialized. The objective function is then evaluated for these individuals. The first/initial generation is produced.

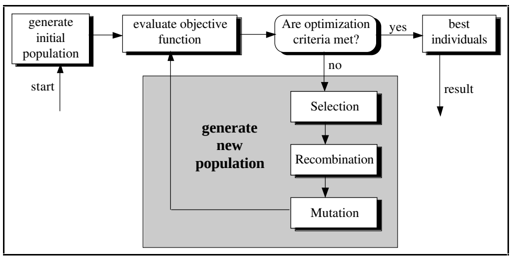

Fig 7: Structure of a single population genetic algorithm

If the optimization criteria are not met the creation of a new generation starts. Individuals are selected according to their fitness for the production of offspring. Parents are recombined to produce offspring. All offspring will be mutated with a certain probability. The fitness of the offspring is then computed. The offspring are inserted into the population replacing the parents, producing a new generation. This cycle is performed until the optimization criteria are reached. The best found individual is the solution, the found optimum. Fig. 7 shows the structure of a simple genetic algorithm.

In natural evolution species tend to reproduce in a neighbourhood and not the whole population. These subpopulations evolve isolated from each other, however, exchange (migration) between subpopulations occurs from time to time. The migration model enhances the results of the genetic algorithm compared to an algorithm with one population.

All computations were done using *MATLAB* and the *Genetic Algorithm Toolbox for use with MATLAB* [20].

The optimization was carried out using the *Multiple Population Genetic Algorithm* [20]. The following operators and parameters were used:

- linear ranking (selective pressure: 2),
- truncation selection (elitest), generation gap 0.9,
- discrete recombination,
- real valued mutation, mutation rate: 1/number of variables per individual,
- 4 subpopulations with 50 individuals each.
- unrestricted migration every 20 generations,

In an early stage is the employment of competing subpopulations. First experiments showed an enhancement of the solutions. However, the presentation of these experiments is not in the scope of this paper.

3.2 Representation of individuals and Cost function

Each individual in the genetic algorithm represents the control of the simulation period. As shown in Section 2 the greenhouse climate model can be controlled employing 4 controls. Currently we are using 3 controls: heating, ventilation and CO_2 enrichment. Vapor injection is set to zero all the time.

The controls are discretized at equidistant time points. For the simulation a first order hold is employed to obtain control values between the discretization points. The number of variables per individual can be obtained using eq. 7.

$$NumVar = \left(\frac{SimTime}{ControlStep} + 1 \right) \cdot NumControl; \quad \begin{array}{l} ControlStep = 0.25h \\ NumControl = 3 \end{array} \tag{7}$$

A control step every 15 minutes is small enough for the simulation and keeps the number of variables as small as reasonable. Thus, for a simulation time of 2 hours an individual consists of 27 variables.

To keep the number of variables and the optimization time handlable we normally employed a simulation period of 2 hours. To optimize longer time periods the optimization was divided into 2-hour-pieces and the end states of one simulation were used as start values of the next period. Thus, arbitrary long simulation periods could be computed using standard hardware (PC Pentium, 16MB RAM).

The cost function that we employ in our model is the maximization of profit, see eq. 6, under fulfillment of all constraints, see Section 2.4. As the Genetic Algorithm Toolbox optimizes by minimization in eq. 8 the profit is multiplied by -1. To enforce the constraints the cost function assigns a penalty to individuals which do not meet the defined constraints.

$$Cost = -\int_{T_S}^{T_E} GEWI\, dt + Penalty \tag{8}$$

We utilize a weighted sum penalty function. *Val* is either one of the state variables of the greenhouse climate or a control value, *Constr* the corresponding constraint. In choosing the weights *W* the importance of every constraint can be defined.

$$Penalty = \sum_{i=1}^{NumConstr} \left(W_i \cdot \int_{T_S}^{T_E} \left| \left(Val_i - Constr_i \right) > 0 \right| dt \right) \tag{9}$$

3.3 Incorporation of domain specific knowledge

First optimizations of the greenhouse climate model were done without using any problem specific heuristics. But, the computation could be accelerated considerably by incorporating domain specific knowledge.

In a standard genetic algorithm the initialization of the individuals is done uniform at random in the domain of every variable. We employed a special initialization function. The initialization of the variables of the individuals was restricted to a small band of the domain. This band was defined from heuristic experience for standard weather conditions of the respective day. During optimization the recombination and mutation operators worked still over the whole domain of the variables.

Using this special initialization we obtained better solutions for the control values and in a smaller number of generations.

Currently we are investigating further methods. One is changing the domain of the variables depending on time of year. For example, in winter the range of ventilation is much smaller than in summer and reverse for heating. Thus, we could further narrow down the search and enhance the guiding of the genetic algorithm. However, this method is very problem specific and could not be easy generalized. Another possibility is the use of other heuristics known from practice. If heating is high ventilation is not really useful, the same is true for CO_2 enrichment and vice versa.

All this shows, that the genetic algorithm is only one part of the optimization algorithm. Especially if online response time requirements in practical use of the model and optimization should be met all possibilities for enhancing the control must be used.

4 Experimental results

The approach of this reports is new compared to previous publications about the control of greenhouse climate. In [3], [10] and [22] the control by CO_2 enrichment is described, [17] shows the effect of night temperature control. [15] describes a greenhouse climate model as well, however, only the consequence of different set points for temperature or CO_2 is investigated by simulation.

The integrated model of all components of the greenhouse opens new possibilities for optimal control reaching one step ahead of previous work. Using the described model and optimization (genetic algorithms) we can derive an optimal solution for the control. Thus, the system finds the best solution over the simulation period and can be used for profit maximization or the prevention of stress for the plants. This is especially useful for online control or/and changing environment conditions.

The first Subsection shows the optimal control of typical days in April and June. Afterwards, the change of optimal control in dependence of changing fruit and/or energy price in February is shown.

The used weather data in this report constitute the average over 10 years for Potsdam, Germany [19]. Therefore, the data is smooth and without disturbances.

The canopy area per square meter is smallest in February (0,5m^2/m^2) and highest in June (2,5m^2/m^2).

4.1 Optimal control for typical days

This Section shows the results from optimization of the greenhouse climate model for typical days in April and June. The prices from Tab. 1 were used for profit calculation.

The left diagram shows the plots for the state variables of the greenhouse: air humidity, *DDI* eq. 2, temperature, *TEMI* eq. 1, and CO_2 concentration, *CI*, eq. 3. The CO_2 concentration was divided by 100 to scale with the other two variables.

The plots of biomass, *BIOM*, and profit, *GEWI* eq. 6, can be seen in the middle plot. The biomass is scaled down by 100 to fit with profit in one plot. The right diagram displays the plots of the 3 control variables: heating, *Q*, ventilation, *LR* and CO_2 enrichment, *W*.

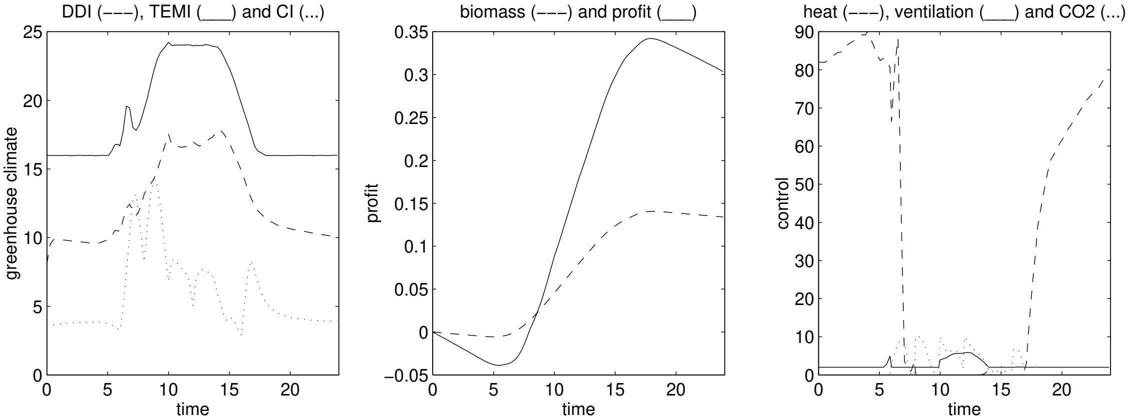

Fig. 8. Results of optimization for April

In April heating is high during the whole night. This ensures keeping temperature around 16°C, the lower constraint of temperature. During daytime heating is not necessary. Ventilation is only on over noon to keep temperature below 24°C, the higher constraint of temperature. As ventilation is low or off during daytime much CO_2 is injected to keep CO_2 concentration high.

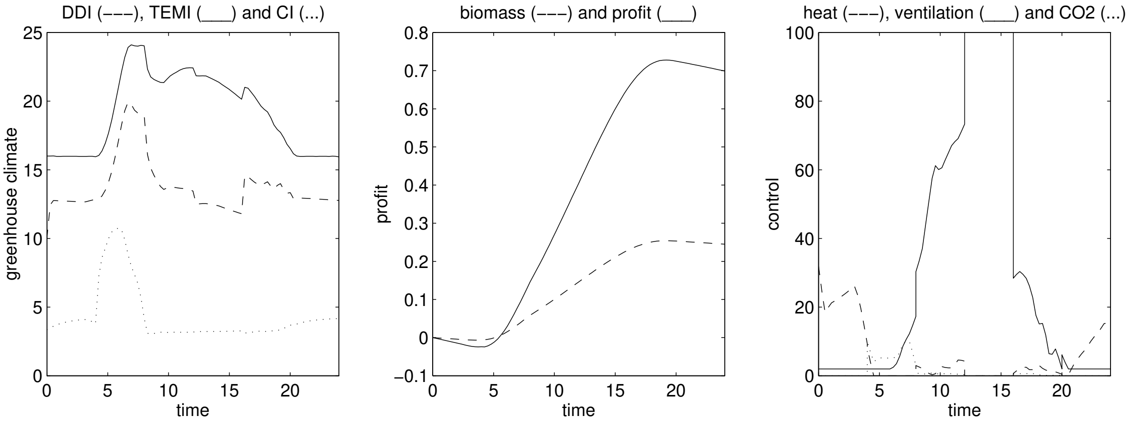

Fig. 9. Results of optimization for June

In June the picture is quite different. Ventilation is on the whole day to keep temperature low. Ventilation is higher on than necessary for keeping temperature below 24°C. A temperature around 20°C is better for production than 24°C (result from simulations not shown here). However, in the morning, when ventilation is still off and the sun is already shinning (sun comes up around 4 o'clock) CO_2 is injected to increase CO_2 concentration and thus biomass production. When ventilation is opened to keep temperature low, CO_2 enrichment is no longer useful. Heating is only on during night to keep temperature above the lower constraint of 16°C.

4.2 Optimal control under changing prices

Until now we worked with constant prices. However, this world is not constant and thus prices are changing as well. For this experiment the price of heating (energy) and CO_2 enrichment was changed from the standard value. Depending on the difference the course of control can change slightly or seriously.

As the used weather data are average data and smooth, we employed two drastic changes to the energy and CO_2 price to show the consequences.

In Fig. 10 the energy and CO_2 price was 3 times as high as standard. The heating is as small as necessary to keep temperature above the lower constraint. During day nearly no CO_2 is injected. Ventilation is never on.

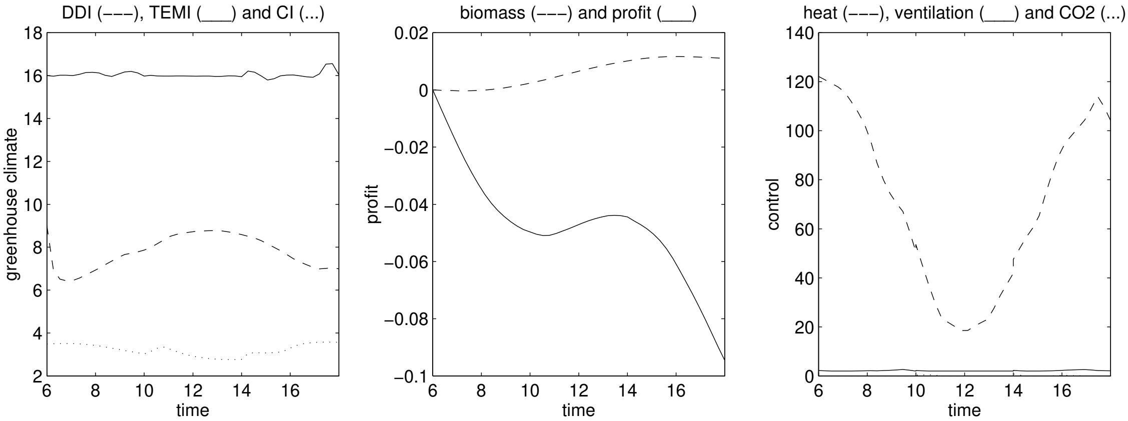

Fig. 10. Results of optimization for February employing high energy and CO_2 price

Employing an energy and CO_2 price 3 times lower than standard price produces a different picture. Now, heating is higher than keeping the lower constraint unviolated. During daytime CO_2 is enriched. The amount of produced biomass (BIOM=1.5) is higher compared to the optimal control employing high prices (BIOM=1.1). Due to the lower price the profit is much higher and positive.

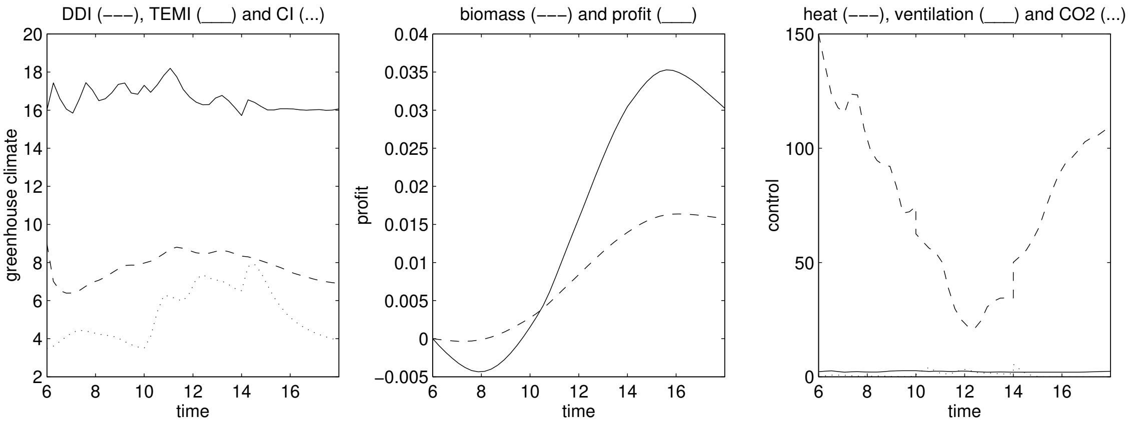

Fig. 11. Results of optimization for February using low energy and CO_2 price

This experiment described the use of the presented system under consideration of changing prices as an example for changing parameters of the model. The system computes still the optimal control of the greenhouse. As all parameters are incorporated into the model they are effective during the very next optimization. This is especially useful during online control - no new strategy should be developed or tested in numerous simulations.

5 Concluding remarks

In this paper we have presented a new genetic algorithm based optimization method to address the control of greenhouse climate employing an integrated model of greenhouse climate, plan, outside weather conditions and control equipment.

The presented model and optimization can directly be used for online control of greenhouses. We presented results of optimization for typical control situations and showed the applicability of the presented method.

In future research we will consider enhanced plant models and for other plants as well. These models are currently in the final validation phase.

We also plan to investigate the influence of enhancements to the genetic algorithm. A promising direction is the use of competing subpopulations. Another area of research is the development of problem specific recombination and/or mutation operators.

References

[1] Bailey, B. J. and Seginer, I.: Optimum control of greenhouse heating. Acta Horticulturae, 254, pp. 512-518, 1989.

[2] Bailey, B.: Climate modelling and control in greenhouses. 173-201, 1991.

[3] Bakker, J. C.: A CO_2 control algorithm based on simulated photosynthesis and ventilation rate. Acta Horticulturae, 174, pp. 387-392, 1985.

[4] Bot, G. P. A.: A validated physical model of greenhouse climate. Acta Horticulturae, 245, pp. 389-396, 1989.

[5] Bot, G. P. A.: Physical modelling of greenhouse climate. The computerized greenhouse, Automatic control application in plant production, pp. 51-73, 1993.

[6] Challa, H. and van Straten, G.: Optimal diurnal climate control in greenhouses as related to greenhouse management and crop requirements. The computerized greenhouse, Automatic control application in plant production, pp. 119-137, 1993.

[7] Chipperfield, A. J., Fleming, P. J. and Pohlheim, H.: A Genetic Algorithm Toolbox for MATLAB. Proc. Int. Conf. Sys. Engineering, Coventry, UK, 6-8 Sept., 200-207, 1994.

[8] Cierpinski, W., Broneske, J., Krüger, I., Kleisinger, S., Herbold, J. und Reisinger, G.: Entwicklung eines Gewächshaussystems mit minimiertem Energiebedarf und minimierter Umweltbelastung. Forschungsabschlußbericht zur Aufgabe BMFT-FB 0329192A, Institut für Gemüse- und Zierpflanzenbau Großbeeren/Erfurt e.V., 1994.

[9] Ehler, N.: An autocalibrating model for simulating and measuring net canopy photosynthesis using standard greenhouse climate computer. Computers and Electronics in Agriculture, 6, pp. 1-20, 1991.

[10] Ehler, N. and Karlsen, P.: OPTICO - a model based real-time expert system for dynamic optimization of CO_2 enrichment of greenhouse vegetable crops. Journal of Horticultural Science, 68, pp. 485-494, 1993.

[11] Heißner, A.: Die Transpiration von Tomatenpflanzen im Gewächshaus in Abhängigkeit vom Dampfdrucksättigungsdefizit der Luft und der Bestrahlungsstärke. Versuchsbericht 93 3 23, Institut für Gemüse- und Zierpflanzenbau Großbeeren/Erfurt e.V., 1993.

[12] Heißner, A.: Gewächshausklimamodell. Programmdokumentation, Institut für Gemüse- und Zierpflanzenbau Großbeeren/Erfurt e.V., 1994.

[13] Houter, G.: Simulation of CO_2 consumption, heat demand and crop production of greenhouse tomato at different CO_2 strategies. Acta Horticulturae, 268, pp. 157-164, 1990.

[14] Jolliet, O.: HORTITRANS, a model for predicting and optimizing humidity and transpiration in the greenhouses. Journal of Agricultural Engineering Research, 57, pp. 23-37, 1994.

[15] Jones, J. W., Hwang, Y. K. and Seginer, I.: Simulation of Greenhouse Crops, Environments and Control Systems. Acta Horticulturae, 399, pp. 73-84, 1995.

[16] Lentz, W.: Numerische Suchverfahren als Hilfsmittel zur Ableitung von Handlungsstrategien aus bioökonomischen Simulationsmodellen. Agrarwissenschaft, 38, pp. 40-50, 1989.

[17] Mayrogianopoulos, G. N.: Dynamic optimization of night temperature in relation to climate control in greenhouse. Acta Horticulturae, 287, pp. 109-116, 1991.

[18] Michalewicz, Z.: Genetic Algorithms + Data Structures = Evolution Programs. Berlin, Heidelberg, New York: Springer, 1992.

[19] Pohlheim, H. and Heißner, A.: Optimierung eines Gewächshausklimamodells: Grundlagen, Verfahren und Ergebnisse. technical report, pohlheim@systemtechnik.tu-ilmenau.de, 1996.

[20] Pohlheim, H.: Genetic Algorithm Toolbox - Documentation. technical report, pohlheim@systemtechnik.tu-ilmenau.de, 1995.

[21] Pohlheim, H.: Genetic Algorithms: Principles, Methods and Algorithms. technical report, pohlheim@systemtechnik.tu-ilmenau.de, 1995.

[22] Seginer, I.: Expected usefulness of CO_2 enrichment and shading in a desert climate. Acta Horticulturae, 268, pp. 149-156, 1990.

[23] Tantau, H. J.: Greenhouse climate control. Proceedings of the international seminar and British-Israel work- shop on greenhouse technology, Bet Dagan, Israel, 26 March-2 April 1990, pp. 91-101, 1990.